Ad Hoc Networks 11 (2013) 1848–1857

Contents lists available at SciVerse ScienceDirect

Ad Hoc Networks

journal homepage: www.elsevier.com/locate/adhoc

On the trade-off between energy efficiency and estimation error in compressive sensing ☆

Donglin Hu [a], Shiwen Mao [a,*], Nedret Billor [b], Prathima Agrawal [a]

[a] Department of Electrical and Computer Engineering, Auburn University, Auburn, AL, USA
[b] Department of Mathematics and Statistics, Auburn University, Auburn, AL, USA

ARTICLE INFO

Article history:
Received 3 December 2012
Received in revised form 20 March 2013
Accepted 8 April 2013
Available online 28 April 2013

Keywords:
Bayesian estimation
Cognitive radio
Compressive sensing
Isotonic regression
Polynomial regression
Spectrum sensing

ABSTRACT

Compressive sensing (CS) refers to the process of reconstructing a signal that is supposed to be sparse or compressible. CS has wide applications, such as in cognitive radio networks. In this paper, we investigate effective CS schemes for the trade-off between energy efficiency and estimation error. We propose an enhancement to a Bayesian estimation approach and an enhancement to the isotonic regression approach that is based on nearly isotonic regression. We also show how to compute the routing matrix for selecting active sensor nodes. The proposed enhancements are evaluated with trace-driven simulations. Considerable gaps are observed between the original approaches and the proposed enhancements in the simulation results. The near isotonic regression method achieves the best performance among all the CS schemes examined in this paper.

1. Introduction

Compressive sensing (CS) (a.k.a. *compressed sensing*) refers to the process of reconstructing a signal that is supposed to be sparse or compressible [2]. It has found wide applications in communications and networking. For example, in cognitive radio networks, spectrum sensing is a critical component in dynamic spectrum access and enforcement of spectrum usage and sharing [3–7]. Given the wide range of activities in space, time, and frequency, it would be extremely challenging and costly to have a full range and dense sampling. In such situations, compressive sensing becomes a powerful tool for efficient spectrum sensing. Generally in a wireless sensor network (WSN), spatially distributed sensors are used to monitor physical or environmental conditions [8,9]. The sparse signals in wireless sensor networks are obtained by collecting readings from sensor nodes by a server (or, a data processing center) through wireless transmissions. The server will then use CS to process the sparse data to achieve certain design goals (e.g., recovering the missing data).

CS has received considerable interest from the wireless community recently. For example, several CS papers have focused on network optimization and scheduling, where two important factors, i.e., *network performance* and *power consumption*, are considered in the design of CS schemes. The objectives of the schemes presented in these papers are to prolong the life time of wireless sensor nodes, while meeting certain network performance requirements. Energy can be conserved by turning off some sensor nodes while keeping the rest active. Network performance can be measured in terms of surveillance quality such as the number of active nodes [10,11], network coverage [12], the minimum degree of connection [13,14], and surveillance delay [15,16]. The proposed schemes usually aim to achieve a trade-off between network performance and power consumption.

☆ This paper was presented in part at IEEE GLOBECOM 2012, Anaheim, CA, USA, December 2012 [1]

* Corresponding author.
E-mail addresses: dzh0003@tigermail.auburn.edu (D. Hu), smao@ieee.org (S. Mao), billone@auburn.edu (N. Billor), agrawpr@auburn.edu (P. Agrawal).

1570-8705/$ - see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.adhoc.2013.04.008

Other CS papers have laid emphasis on signal compression and reconstruction. These papers seek a trade-off between *compression efficiency* and *reconstruction quality*. For instance, the conventional CS approach is based on orthonormal basis. An important example of this approach is wavelet transform. The original sensor data is compressed and delivered [17]; therefore fewer network resource will be needed for transmitting the compressed data [18–20].

In this paper, we investigate effective CS schemes for addressing the fundamental trade-off between *energy efficiency* and *estimation error*. As discussed, a compressed signal can be obtained by collecting readings from a subset of the deployed sensor nodes, so that the rest of the nodes can be turned off to save energy. At the data processing center, the intact signal is reconstructed via signal estimation. Therefore, there is a fundamental trade-off between how many active nodes to choose (thus how much energy to spend) and the corresponding accuracy of prediction. Recently, only a few papers have investigated the problem of joint *network optimization* and *signal processing*. In [21], sensor nodes are divided into subgroups and all the readings can be recovered from one of the subgroups using isotonic regression. The objective is to maximize the number of subgroups while keeping the estimation error below a tolerable threshold. In [22], nodes are grouped into pairs. In each pair, the node with lower battery capacity goes to sleep, while the node with higher battery capacity estimates the measurement of the sleeping node using linear regression. In [23,24], the authors investigate the problem of reconstructing a distributed signal through the collection of a small number of sensor readings, where CS is applied in conjunction with principle component analysis. The data of the entire network is recovered with Bayesian estimation.

In particular, we aim to develop effective CS schemes in WSNs and seek to balance the trade-off between energy saving and recovery accuracy, which are in terms of the number of active sensor nodes and the corresponding estimation error. We examine three classes of CS approaches in related work discussed above. We first implement the Bayesian estimation approach presented in [23], and propose an enhancement to this approach by scaling the variance of the sensor readings. We next revisit the isotonic regression approach presented in [21], and propose an improved method based on nearly isotonic regression. Finally, we briefly introduce two polynomial regression approaches, i.e., linear regression and quadratic regression, which are used as benchmarks in the performance evaluation. Bayesian estimation selects active nodes randomly, while isotonic regression chooses active nodes based on estimation errors, which results in better reconstruction quality. Unlike LR and QR, isotonic regression considers the distribution of readings for more accurate estimation. The proposed enhancements are evaluated with trace-driven simulations. We find considerable gaps between the original approaches and the proposed enhancements in the simulation results. We also find that the near isotonic regression method achieves the best performance among all the CS schemes examined in this paper.

The remainder of this paper is organized as follows. In Section 2, we describe the system model and assumptions. We introduce Masiero's method and its enhancement in Section 3. In Section 4.1, we discuss Koushanfar's method and the nearly isotonic regression based enhancement. In Section 5, we present two polynomial regression schemes. We evaluate the proposed enhancements with trace-driven simulations in Section 6. Section 7 concludes this paper.

2. System model and assumptions

The network model considered in this paper consists of autonomous sensor nodes that are deployed in an area to monitor physical conditions (e.g., spectrum availability) and a data processing center (or, a server), as illustrated in Fig. 1. We assume that the sensor nodes collect information data following a synchronized slot structure. Once a node obtains its data in a time slot, it transmits the data to the data processing center through its wireless interface in the same time slot.

We assume the process of sensing and transmission of one unit of sensor data consumes a certain amount of energy, denoted as E, which is a constant. If there are N sensor nodes deployed, the total amount of energy consumed in each time slot is $N \times E$. It is easy to see that a convenient way to conserve energy for the WSN is to reduce the number of active sensor nodes. On the other hand, the data from the idle nodes has to be recovered through CS to ensure certain precision of detection. The estimation errors of the recovered data should meet the minimum precision requirement of the target sensing application. Therefore, *there is a fundamental trade-off between the number of active nodes and estimation error*.

In the following sections, we introduce three classes of CS approaches and propose enhanced algorithms. The first class is *Bayesian Estimation* approaches, which focus on energy saving by managing the number of active sensor nodes. Specifically, L active sensor nodes will be chosen from the set of N sensor nodes to collect sensing data in each time slot. The second class includes the *Isotonic Regression* approaches and the third class is *Polynomial Regression* approaches, which guarantee the quality of recovered data by controlling the estimation error. With these techniques, we choose as few active sensor nodes

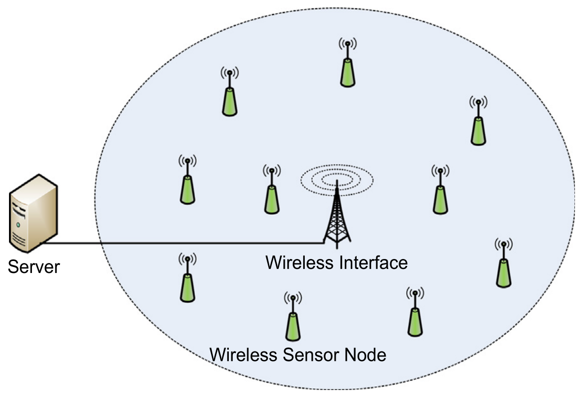

Fig. 1. The wireless sensor network model.